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THE CHALLENGES AND POSSIBILITIES OF LONG-TERM SELF-MONITORING OF HEALTH

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ABSTRACT

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This thesis explores the challenges and possibilities of long-term self-monitoring of health. Self-monitoring of health can include tracking parameters, such as activity, weight, body composition, heart rate, blood pressure, and pulse wave velocity. These parameters and self-monitoring technologies are introduced. The effects of long-term self-monitoring reported in literature are reviewed in order to compose an overview of the benefits and challenges associated with long-term self-monitoring of health. Long-term self-monitoring of health has the potential to lead to improvements in well-being and health. However, unwillingness to self-monitor and early abandonment of self-monitoring devices are deterrents to self-monitoring. Factors, such as effort required, technical difficulties, unreliability of results, perceived uselessness of collected data, and privacy concerns, contribute to early abandonment.

The observations about self-monitoring made by one participant during a two week period of self-monitoring with an activity tracker, smart scale, and blood pressure monitor are compared to those reported in literature. In line with literature, the participant reported technical difficulties, perceived uselessness, and unreliability of data, which all discouraged use of the devices. However, unlike findings reported in literature, the participant did not observe self-monitoring to noticeably improve their health or affect their well-being. This could be explained by receiving consistently healthy values from measurements and thus not seeing the need for any type of behavioral change that would improve health or well-being.

Keywords: Self-monitoring, health tracking, long-term, personal health devices

The originality of this thesis has been checked using the Turnitin OriginalityCheck service.

CONTENTS

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LIST OF SYMBOLS AND ABBREVIATIONS

AC	Alternating current
alPTT	Aorta-leg pulse transit time
BCG	Ballistocardiography
BIA	Bioelectrical impedance analysis
BMI	Body mass index
BP	Blood pressure
bpm	Beats per minute
CST	Consumer sleep technology
DC	Direct current
ECG	Electrocardiogram
HR	Heart rate
LED	Light emitting diode
PPG	Photoplethysmography
PWV	Pulse wave velocity

1. INTRODUCTION

A sedentary lifestyle has been shown to adversely impact quality of life and mental health, and is considered to be a significant risk factor contributing to chronic diseases, such as cardiovascular disease and diabetes. Despite this, over a quarter of the worldwide population fail to achieve the recommended weekly amount of either 150 minutes of moderately intense activity or 75 minutes of vigorous activity. [1] Thus, there has been an increased interest and supply for tools that aid individuals in analysing their current lifestyle, in recognizing unhealthy and problematic behaviour, and in motivating them to change their behaviour for the better.

Self-monitoring of health could be a useful tool for this purpose since it allows individuals to be increasingly included in the management of their health through objectively monitoring relevant health related parameters. Self-monitoring of health refers to the process of systematically observing and recording health-related parameters and behaviour [2]. Usually this is done with the use of wearable devices for continuous measurements or other consumer grade devices used at home for single measurements. For a long time self-monitoring has been utilized mostly by fitness enthusiasts or as a tool in the management of chronic diseases. However, the relatively recent advances in the availability of consumer grade personal health devices has increased self-monitoring also among normal healthy people. [3]

Self-monitoring can include tracking activity, weight, diet, sleep, blood pressure (BP), mood, stress levels, or disease symptoms. The possibilities of self-monitoring are immensely broad, and each individual chooses what they want to track. The possibilities are continuously increasing as new consumer grade personal health devices or health related smart phone applications are introduced to the market. [4] Now, many functions of devices traditionally found only in health care settings are beginning to be available for consumers to use at home.

This thesis explores the possibilities and challenges of long-term self-monitoring. This thesis has two objectives. The first objective is to evaluate whether long-term self-monitoring of health affects well-being, and the second objective is to identify the challenges associated with long-term self-monitoring. This is done by conducting a literature review of studies exploring areas of self-monitoring and assessing the results in relation to well-being. In addition, the reported challenges are reviewed. The thesis also includes a short experimental simulation of active self-monitoring of health with the use of common self-monitoring devices, an activity tracker, a smart scale, and a BP monitor. The purpose of the simulation is to provide an experimental perspective. The focus during this simulation is on observing the effect of self-monitoring on behaviour and well-being. Additionally, the goal is to identify all the personally perceived benefits and challenges associated with active self-monitoring.

The thesis first introduces the concept of self-monitoring of health. Chapter 2 gives an overview of common self-monitoring parameters, the technology used for tracking these, and devices available for consumers. Chapter 3 discusses long-term self-monitoring in terms of its effect on well-being and the observed benefits and challenges associated with long-term self-monitoring. Chapter 4 introduces the experimental setup used for the active self-monitoring simulation. The results of the simulation are presented in Chapter 5. Chapter 6 discusses the results and how they compare with literature. Finally, Chapter 7 presents the conclusions of this thesis.

2. SELF-MONITORING OF HEALTH

Self-monitoring of health is an individual's process of tracking health related metrics or behaviour. These include but are not limited to tracking activity, weight, body composition, heart rate (HR), sleep, BP, and food intake. Since there are a significant amount of health related metrics and behaviour, self-monitoring of health is a broad concept.

Although self-monitoring of health is mostly used as a personal tool for assessing and maintaining well-being, self-monitoring is also an important part of the management of some chronic diseases, such as diabetes and hypertension. However, the focus of this thesis is on the areas that are most commonly monitored by the average population. Thus self-monitoring, such as blood glucose monitoring, that is commonly used only for disease management is omitted.

While pen and paper are common self-monitoring tools, self-monitoring now heavily relies on the use of personal health devices and software to collect and display data. This section introduces the parameters and behaviour related to health that are commonly monitored and the commercially available technology for monitoring them. The areas of self-monitoring that are introduced are activity, weight, body composition, sleep, HR, BP, and pulse wave velocity (PWV). With the exception of BP monitors, the devices available for consumers for the purpose of self-monitoring the aforementioned parameters are generally not medical devices.

2.1 Activity

A sedentary lifestyle is considered to be a substantial health risk, and regular physical activity has been linked to both physical and mental health benefits. Self-monitoring technology is a commonly used tool to promote activity. [5] Self-monitoring of activity has become increasingly popular with wearable technology such as activity or fitness trackers [6]

Activity is monitored by measuring movement with inertial sensors [7]. Inertial sensors used in activity trackers include accelerometers, gyroscopes, magnetometers, and barometers or altimeters [7, 8]. Currently, the most common inertial sensor in activity trackers is an accelerometer [8]. It is an instrument that measures movement by measuring acceleration [9].

An accelerometer measures the acceleration of the moving object it is connected to. A single accelerometer can detect acceleration in one predefined direction that depends on the orientation of the accelerometer. A typical accelerometer is composed of a seismic mass, spring, damper, and a sensor. The spring, damper, and sensor are used to connect the seismic mass to the accelerometer housing connected to the object. Acceleration of the object causes relative motion between the seismic mass and the accelerometer housing, which is detected by the sensor. The sensor can be a strain gage, piezoelectric element, or a capacitive element. [10]

Commonly an accelerometer used for activity monitoring has a piezoelectric element [9]. This is because piezoelectric elements are able to generate large outputs compared to their size. [10] Thus, they can be used in smaller applications. A schematic of a sample piezoelectric accelerometer is shown in Figure 1. The accelerometer contains a seismic mass connected to the accelerometer housing through a spring, damper, and a piezoelectric crystal. When the accelerometer is subjected to acceleration, the displacement of the mass causes strain to the piezoelectric crystal. Due to the piezoelectric effect, this allows a charge to flow through the piezoelectric crystal between the conductive coatings. The charge is proportional to the strain experienced by the piezoelectric crystal, and thus the displacement of the mass. [10]

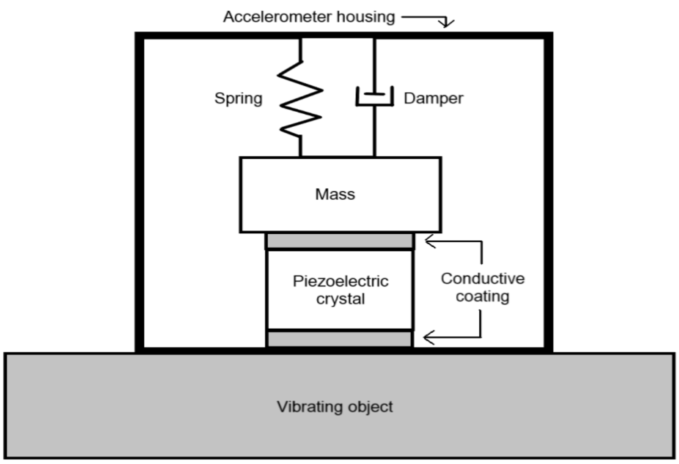

Figure 1. *A schematic of a piezoelectric accelerometer. The piezoelectric accelerometer consists of a seismic mass connected to the accelerometer housing by a string, damper, and a piezoelectric crystal. Figure adapted from [10].*

Activity trackers usually utilize triaxial accelerometers, which measure acceleration in three orthogonal directions [8]. In some activity trackers, gyroscopes and magnetometers are used together with an accelerometer to achieve more accurate motion tracking [7]. A gyroscope measures gravitational acceleration, which is used to detect orientation and angular velocity. A magnetometer measures the strength and direction of detected magnetic fields, which can be used to determine orientation in relation to the magnetic north of earth. [8]

Additional sensors are used in order to increase device accuracy [8] However, since gyroscopes have a high power consumption compared to accelerometers, they are not as appealing for wearable battery powered devices [7]. For this reason they are not found in every activity tracker, but are mainly used in applications that demand more accurate measurements, such as more expensive sports trackers.

Similarly barometers or altimeters, which are not essential for activity detection, can be found in some devices. Barometers or altimeters are used to determine altitude and altitude changes. These sensors can be utilized to provide additional metrics in activity trackers, for example the number of floors climbed. [8] Additionally, they can be useful in specialized applications, such as sports trackers designed for mountain climbing.

Some combination of these inertial sensors used to measure movement are embedded in smart watches or activity trackers that can be used to track parameters such as number of steps, distance, and calorie consumption. These metrics are all calculated by algorithms from the measured movement data and often personal information from the user, for example weight, height, and age. The data collected by activity trackers can often be accessed in real time from the activity tracker or from a companion smart phone application. [8] Additionally, these types of sensors are also embedded into modern smart phones. Thus, smart phone applications can be used to track activity. Often these applications can be downloaded into the phones free of charge, making them a convenient and cheap option for activity monitoring. [6]

2.2 Weight and body composition

Self-monitoring of weight has been shown to be an effective tool in weight loss and maintenance [11]. Traditionally self-monitoring of weight has been performed with the use of a scale and a paper diary. However, technological advances have provided further options. While weight is still measured using a scale, the measurements can be logged into smart phone applications. The use of smart scales even enables measurement data to be synced with an application automatically, reducing effort required from the user. Often smart phone applications display the measurements as graphs over time, giving a quick overview of weight history. This enables the user to easily monitor their progress. Furthermore, applications can be used to set reminders for regular measurements, which improves adherence.

An excessive amount of body fat is linked to several medical issues [12]. Body composition describes what the body is composed of. The simplest methods estimate the amount of fat mass and lean mass while more complex methods can determine more in detail the different components of lean mass, such as muscle and bone mass. [13] The body mass index (BMI) is a simple method commonly used to estimate fat mass and determine if a person is of a healthy weight considering their height. The commonly used equation is

$$\mathrm{BMI} = \frac{\mathrm{Weight}}{\mathrm{Height}^2},$$

in which weight is in kilograms and height is in meters. In the equation, the height is squared in order to decrease the effect of leg length since the majority of fat mass is situated in the torso. [12]

However, BMI does not accurately represent the amount of body fat. For example, a person with a low body fat percentage may have a high BMI. Body fat measurements are a solution for this. There are several technologies used to estimate body fat. Body fat can be estimated by underwater weighing, air displacement plethysmography, bioelectrical impedance analysis (BIA), dual-energy x-ray absorptiometry, and measurements of skin-fold thickness from different sites. [12] Most of these measurement methods are not feasible for self-monitoring purposes. Of the aforementioned techniques, only BIA and measurement of skin-fold thickness are convenient for self-monitoring at home. The other techniques require significantly more expensive equipment and a laboratory setting with trained professionals [13].

The measurement of skinfold thickness gives a measure of subcutaneous fat. Callipers are used to measure skinfold thickness at different body sites, such as the biceps, suprailiac, and subscapular. An estimation of fat mass is derived using age and gender specific algorithms. There are different algorithms that utilize measurements from different sites. While this method is inexpensive, it is associated with low accuracy. The most notable error sources include skill, type of callipers, and the algorithm. [13]

BIA is based on the differing electrical conduction properties of different tissue types in the body. The measurement is performed using surface electrodes to transmit an electric current through the body and measure the electrical impedance of the body in response to the current. Lean tissue is a better conductor than fat tissue, since lean tissue contains water and electrolytes. Fat tissue does not contain water, making it a poor conductor. [13] Thus, the measured impedance reflects the amount of water in the body. Algorithms are used to predict fat free mass based on the measured impedance. These algorithms generally utilize the assumption that lean tissue has a hydration factor of 0.73. With this assumption, the amount of fat free mass can be predicted. Finally fat mass can be calculated from the difference of weight and fat free mass. [14]

BIA is a relatively low cost and rapid method for body composition measurement. It is portable and does not require a laboratory setting. Thus, it is a convenient technology for measurements at home, and has been implemented into some smart scales on the market. Despite all the advantages of BIA, it is an indirect measurement technique. This means that algorithms must be used to predict the wanted quantity. The use of algorithms requires assumption of values. Furthermore, these algorithms have been constructed with population mean values, but are applied on a measurement of an individual. Because an individual is seldom a perfect reflection of the population mean, this results in prediction error. Additionally, different devices may not provide identical measurements as the algorithms are not standardized. [14] Thus, measurements with different devices are not necessarily comparable. However, if the same device is continuously used, as is common in at home self-monitoring, at least the measurements can be used to review progress.

2.3 Sleep

Sleep is considered to have a substantial impact on health and well-being. Poor sleep is associated with depression, anxiety, fatigue, and inability to focus. In the long-run insufficient sleep can negatively impact health, for example by indirectly contributing to obesity, diabetes, cardiovascular disease, or a cold. The perceived importance of sleep acts as a motivator for self-monitoring. [15]

Consumer sleep technology (CST) is technology that is used to self-monitor sleep and is available for consumers without prescription. CSTs include smart phone applications, wearable devices, and embedded devices. [16] The smart phone applications do not require any additional sensors, they use the built in sensors of the phones. Sleep tracking applications can utilize the microphones, cameras, and inertial sensors of smart phones. The microphone can be used to record audio in order to detect snoring, sleep talking, and even identify respiratory patterns. The camera can be used to visually detect sleeping behaviour and inertial sensors are used to track movement. [17] While the features differ from application to application, some common features are sleep tracking, smart alarms, and sleep logging. In order to perform sleep tracking, many of the applications require the smart phone placement on the sleep surface, and use the built in accelerometers to measure movement from the sleep surface. The detected movements are used to determine when the user is asleep and estimate the depth of sleep, usually a determination between light and deep sleep. [16]

Wearable sleep monitoring devices, such as activity trackers, use the same accelerometers that are used to measure activity to track sleep. Similarly to the smart phone applications, the detected movements are analysed in order to determine depth of sleep. Some devices also incorporate HR, respiratory pattern, and temperature monitoring to improve accuracy. [16] Wearable sleep monitoring devices are mostly wrist-worn activity trackers or smart watches, but there are also clip based applications and even a shirt capable of sleep monitoring. [18]

Embedded devices used for sleep monitoring are devices that are embedded into the sleeping environment [16]. Examples of embedded devices include cameras in the sleeping environment and devices, such as Beddit and EarlySense, which utilize embedded sensors in the sleep surface, either on top or under the mattress [16, 18]. Mattress-based devices detect respiration patterns, movement, and apply ballistocardiography (BCG) for cardiac monitoring. BCG utilizes the measurement of small movements of the body caused by the pulsatile ejection of blood from the heart during systole. [18]

While especially the smart phone applications have ambitious claims, such as the detection of obstructive sleep apnoea or periodic leg movement syndrome, the applications are not scientifically valid [17]. The validation of sleep monitoring devices and applications is performed by comparing them with polysomnography, which is considered the golden standard of sleep monitoring [19]. There is a significant lack of validation of CST technology and especially smart phone applications have been found to be inaccurate compared to laboratory grade measurements [17]. While wearable CST devices are able to accurately detect sleep duration, they cannot accurately determine periods of light and deep sleep [19].

2.4 Heart rate

HR, the number of times the heart beats each minute, is an indicator of physical fitness and health. HR is affected by internal and external factors, such as stress, sleep, and activity. Monitoring HR is used to monitor physical activity and stress levels. Additionally, HR monitoring is widely used to control training intensity in order to accomplish desired training effects. [20] There are two HR monitoring technologies that are common in consumer grade devices. HR monitors are based on either an electrocardiogram (ECG) or photoplethysmography (PPG). The technology depends on the type of HR monitor. Wrist-worn HR monitors are based on PPG and chest strap HR monitors on ECG. [8, 21]

The other method of measuring HR used in consumer grade devices is based on ECG. Two electrodes worn on a chest strap are used to detect the electrical activity of the heart [21]. Compared to a conventional 12-lead ECG, the number of electrodes is small but the measurement principle is the same. Since the purpose is to only determine the interval between heartbeats and the overall quality of the waveform is not as important, one lead is sufficient. An ECG signal is shown in Figure 2.

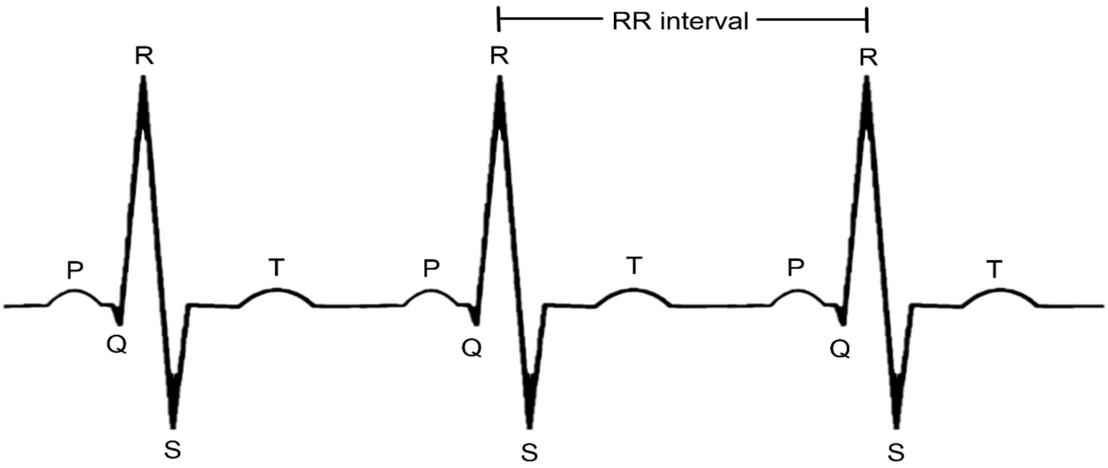

Figure 2. *The waveform of an ECG signal. The RR interval is used to determine HR from an ECG signal.*

The ECG signal contains distinct waves that are detected with every heartbeat. Since the R waves are most prominent, it is easiest to use them in the measurement of HR. The RR interval is used to detect HR. The RR interval is the time interval between the peaks of consecutive R waves.

PPG is an optical technique used for HR monitoring via non-invasive blood volume change measurements. This technology is often implemented into activity trackers and sports watches. PPG uses light-emitting diodes (LEDs) to transmit light into the body. This light undergoes reflection, absorption, and scattering caused by tissue and blood before being detected by a photodetector. [22] There are two operational modes that depend on the positioning of the LED and photodetector. In transmission mode, the LED and photodetector are on opposite sides of a sample tissue, and the photodetector is used to detect the intensity of transmitted light. In reflection mode, the LED and photodetector are on the same side of the sample tissue, and the photodetector is used to detect the intensity of reflected light. Transmission mode is restricted to measurement sites that are thin so that transmitted light can still be detected. [23] Thus, reflection mode is used in wrist-worn devices.

The blood volume in arteries changes according to the cardiac cycle. During systole, as the heart pumps blood into the body, the volume of blood in the arteries increases. This results in an increased absorption of light. After this the volume of blood decreases as the blood travels back to the heart. [23] The intensity of the transmitted or reflected light measured by the photodetector varies according to these cyclical changes in blood volume under the sensor [22]. A photodetector is a sensor that converts the energy of the incident light photons into an electrical signal that is proportional to the total energy of the incident photons, which represents the intensity of the incident light. The resulting voltage signal has two components, the alternating current (AC) component, and the direct current (DC) component. This PPG waveform is shown in Figure 3. The AC component represents the variations in blood volume, and the DC component is the voltage offset caused by the constant absorption and scattering caused by tissues through which the light travels. [22] HR is determined from the measured waveform by calculating the time interval between two consecutive peaks.

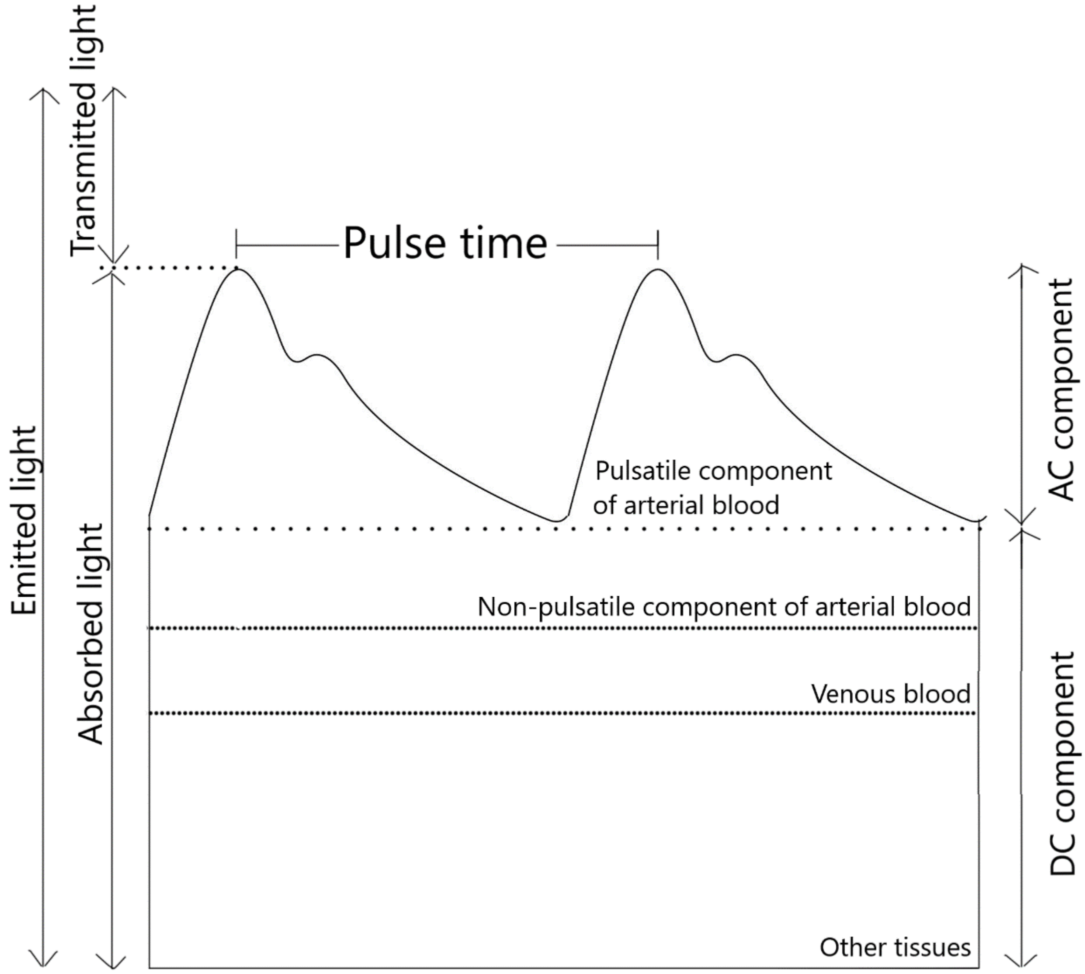

Figure 3. *An illustration of a PPG waveform and its components caused by the tissues and blood through which the light travels. The unchanging components (venous blood, non-pulsatile component of arterial blood, and other tissues) cause the DC component. The AC component is caused by the pulsatile component of arterial blood. HR is determined from the time interval between two consecutive peaks of the AC component. Figure adapted from [24].*

The measurement of PPG is based on the differences in the amounts of absorption and reflection experienced by the different wavelengths, which depend on tissue properties. The light used in PPG is of a wavelength that experiences little absorption in other tissues compared to absorption in blood. This results in blood volume changes causing greater variations in the intensity of the light, making measurements more accurate. Generally red, infrared, or green light have been used in PPG applications. Green light experiences more absorption in both deoxygenated and oxygenated blood and consequently provides more accurate measurements in HR detection applications. [23] For this reason, most commercial HR monitoring devices use green light [24].

Errors in PPG measurements can arise from poor contact between the sensor and skin, and PPG is easily subject to motion artefacts that can affect the detected HR. Generally, chest strap HR monitors based on ECG are considered to provide higher accuracy compared to wrist-worn PPG devices. However, the required chest-strap reduces usability and comfort. [24] Thus, chest strap HR monitors are unsuitable for continuous use. Thus, chest strap HR monitors are mostly used in HR rate monitoring during exercise and not continuously like wrist-worn devices.

In addition to wrist-worn activity trackers that utilize PPG to measure HR and chest strap HR monitors, smart phone applications have been developed for HR monitoring purposes. Smart phone application based HR monitoring can utilize either contact PPG or non-contact PPG. Contact PPG measures HR from the user's finger placed on the camera of the smart phone. This is done by using the flash of the camera as a light source and the camera as the detector. Non-contact PPG measures HR from the face, using only ambient light. [25] While these applications provide an inexpensive HR monitoring alternative, it is not suitable for continuous monitoring for example during exercise. In addition, the performance of these smartphone applications is questionable. Studies have shown significant differences in measurement accuracy between different applications. While some applications have been found to provide acceptable measurement accuracy, the comparison of smart phone application measured HR to ECG and pulse oximetry measured HR detected absolute differences in a significant portion of measurements to be beyond 20 beats per minute (bpm). [25]

2.5 Blood pressure

BP refers to the pressure that blood applies on blood vessel walls. In general, the term BP is used to specifically refer to the pressure in the brachial artery in the upper arm. This pressure varies periodically between the systolic and diastolic pressure according to current stage of the cardiac cycle. Systolic BP is the maximum BP, which occurs after the contraction of the left ventricle of the heart, while diastolic BP is the minimum BP, which occurs after the relaxation of the heart. [26]

Hypertension, which refers to high BP, is a significant factor contributing to cardiovascular diseases, which are the most prevalent cause of death worldwide [27]. Hypertension is also common. For example, in the United Kingdom, the United States of America, and Australia, over a quarter of the population suffer from hypertension. [26] Self-monitoring has been shown to lead to decreases in BP for hypertensive patients [27], making it beneficial for hypertension management. However, it could also aid in the early detection and prevention of hypertension among the healthy population.

BP monitors are medical devices. Self-measurement of BP is performed with an automatic BP monitor. The American Heart Association and the British and Irish Hypertension Society recommend the use of devices that measure BP from the upper arm [28, 29]. Upper-arm BP monitors available for use at home by an untrained user use the oscillometric technique to measure BP [30].

In an oscillometric BP measurement, a pneumatic cuff is placed firmly around the upper arm. In the beginning of the measurement, the cuff is automatically inflated to a pressure higher than the systolic pressure. As the cuff is gradually deflated to a pressure below diastolic pressure, the pressure oscillations in the cuff are detected by pressure sensors. [26] The resulting waveform is illustrated in Figure 4.

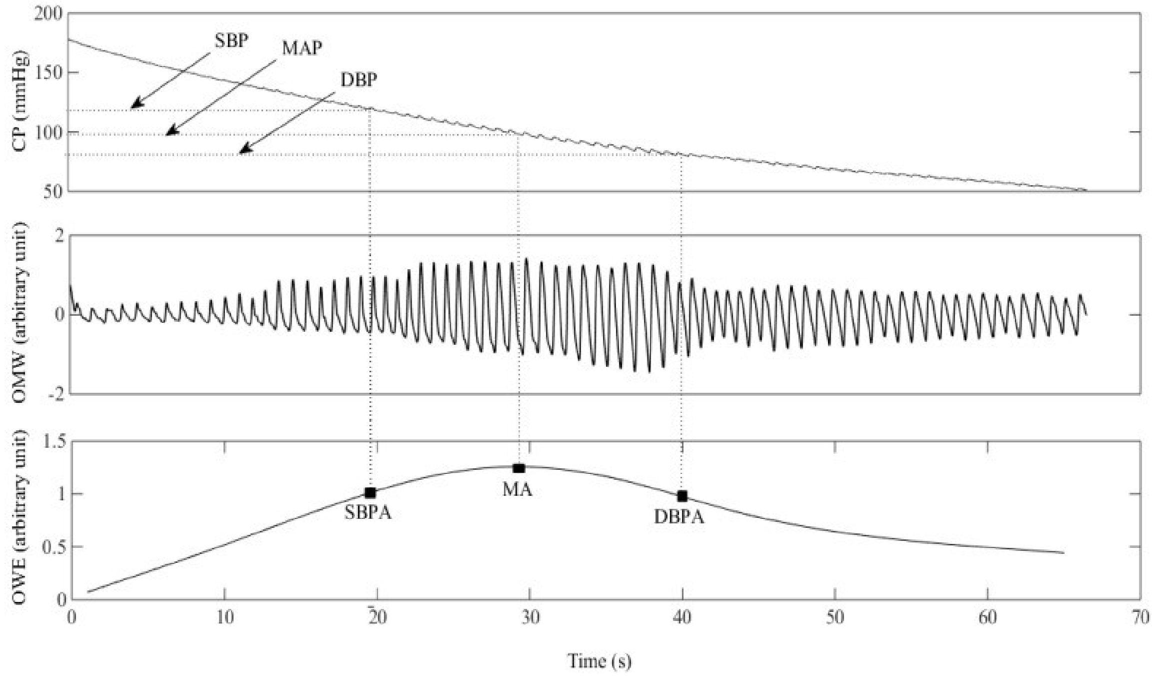

Figure 4. *The oscillometric waveform (OMW) and oscillometric waveform envelope (OWE) that correspond to the decreasing cuff pressure (CF). SBP, DBP, MAP refer to systolic BP, diastolic BP, and mean arterial pressure respectively. The corresponding terms in the oscillometric waveform envelope (SBPA, MA, and DBPA) refer to the amplitude of the oscillometric waveform envelope that corresponds to the relevant pressure. Figure from [31].*

In the beginning, the pressure in the cuff is higher than the systolic pressure. This results in the collapse of the brachial artery, which leads to a situation with no blood flow. At this point the cuff pressure does not oscillate. As the pressure in the cuff is decreased below systolic pressure, blood will begin to flow. However, the blood flow will be restricted until the cuff pressure drops below diastolic pressure. When restricted blood flow is present, the cuff pressure experiences small oscillations in synchrony with the volume changes of the brachial artery. This oscillation begins when the cuff pressure decreases below systolic pressure and increases until reaching maximum oscillation at mean arterial pressure. After this the oscillations decrease. The recorded pressure changes in the cuff are filtered to obtain the oscillations, from which the systolic and diastolic pressures can be estimated with the use of algorithms. [32] Often these algorithms utilize analysis of the oscillometric waveform envelope, which is illustrated in Figure 4. The algorithms vary between manufacturers and are not disclosed to users [26].

The oscillometric technique can also be used to measure BP from the wrist. These devices are usually smaller in size and can be used in cases that upper-arm measurements are not possible. The measurement principle remains unchanged. However, since the systolic and diastolic pressures do not remain unchanged along the arterial tree, additional algorithms must be used to convert the measured pressures to correspond with standard measurements. Several wrist based blood measurement devices have been validated, and are considered to provide acceptable readings when used correctly. However, wrist monitors are more prone to inaccuracies due to user errors, such as incorrect wrist placement in relation to the heart. For this reason, wrist monitors are considered unreliable compared to upper-arm monitors. [30]

2.6 Pulse wave velocity

Since cardiovascular diseases are a leading cause of death, there is a continuous demand for the development of tools that can be used in early diagnosis and detection of risk factors. PWV is the propagation velocity of a pressure pulse originating from the heart. [33] It is used to assess arterial stiffness and predict risk of cardiovascular diseases [34].

PWV can be measured regionally or locally. Regional measurements are performed in two arteries, for example the carotid and femoral arteries. They determine an average PWV for the long segment consisting of several different arteries between the measurement sites. Contrarily, local measurements are used to measure PWV in a short segment of one artery. This type of measurement is a better indicator of arterial stiffness as the average might hide variations. [33]

While technologies, such as angiography, magnetic resonance imaging, and ultrasound are used to measure PWV in clinical settings, these technologies are considered expensive and require operational training [33]. For this reason these technologies are not feasible for self-monitoring purposes. Novel non-invasive PWV measurements make it possible to perform PWV measurements outside clinical settings [34]. These commercial devices measure PWV through regional measurements [33].

Withings has developed a smart scale that measures PWV with the use of impedance plethysmography and BCG. BCG is used to measure the miniscule changes in body weight caused by the pulsatile ejections of blood from the heart during systole. This is used to determine the beginning of systole. IPG is used to measure changes in blood volume. This is done by using thin electrodes on the surface of the scale to apply a current between two parts of the foot. The tissues in the human body act as a conducting electrolyte with a fairly constant conductivity. Blood is a better conductor than the surrounding tissue, so variations in blood volume will affect conductivity, and thus the measured impedance. This is used to determine when the pressure pulse originating from the heart arrives in the foot. The time difference between the beginning of systole and the arrival of the pressure pulse in the foot is known as the aorta-leg pulse transit time (alPTT). This can be used to calculate PWV when the pressure pulse has travelled a known distance. [35]

The combination of IPG and BCG has been shown to provide acceptable estimations of PWV compared to clinical measurements [35]. However, a PWV measurement performed by a smart scale still has limitations [34]. In order to determine PWV from alPTT, the carotid-femoral distance must be known. Since this distance cannot be measured by the user, it is estimated based on the user's self-reported height. [35] Additionally, the technology requires immobility during the measurement and relies on the stability of the user. Thus, acquiring a successful measurement may require several attempts from the user. [34]

3. LONG-TERM SELF-MONITORING

Long-term self-monitoring of health with the use of consumer grade personal health devices could offer significant opportunities in preventing illnesses and improving well-being and health [3]. This chapter explores the benefits and challenges of long-term self-monitoring.

3.1 Benefits of long-term self-monitoring

Long term self-monitoring can be a useful tool in several ways. It can be used to improve understanding of personal behaviour, identifying trends in health related parameters, and motivating behaviour change, which ultimately lead to improved well-being and health [3]. According to research on the effects of long-term self-monitoring, at least the self-monitoring of activity and weight have been associated with health benefits [36, 37].

The long-term use of activity trackers has been found to motivate users in behavioural monitoring, and in improving fitness and health [37]. Studies have found that the use of activity trackers results in an increase in physical activity [5, 37, 38]. This exhibits the motivational quality of self-monitoring that can be used to implement behaviour changes. Self-monitoring applications are able to increase motivation for example through appropriate feedback and the gamification of self-monitoring [4, 39]. The increase in physical activity happens as a result of healthier changes in behaviour, such as taking the stairs when possible or replacing car use with walking. Increased physical activity as a result of long-term use has been shown to also result in long-term benefits, such as improved physical and emotional heath, less pain, and increased independence in older users. [38]

Long-term self-monitoring has been shown to be an effective weight management tool in weight loss and maintenance [11, 36]. Frequent self-monitoring of weight increases awareness of behavior resulting in weight changes and enables detection of small weight changes [11]. Detecting small weight changes makes it easier to reverse them and prevent significant weight gain [36]. While regular self-monitoring is associated with successful weight management, breaks from self-monitoring have been shown to lead to increases in weight. Since weight management is a life-long process, long-term self-monitoring in weight management is beneficial. [11]

Self-monitoring is also an essential part in the management of chronic diseases, such as diabetes and hypertension. In disease management, the benefits of long-term self-monitoring are significant, as self-monitoring can help avoid further health problems, complications and even death. [40] Self-monitoring allows more involvement in disease management, which has been shown to lead to increased medication adherence, better symptom management, and improved health and quality of life. [27, 40].

While the benefits of self-monitoring health related parameters seem to mostly be related to health and well-being, there can be some more unexpected benefits. For example, in some places self-monitoring can even lead to monetary benefits. Some health and life insurers have launched programs that reward uploading self-monitoring data with lower payments. [41]

3.2 Challenges of long-term self-monitoring

In order to achieve any positive benefits through self-monitoring, the individual must be willing to self-monitor. There are several factors, such as scepticism, price, privacy concerns, perceived usefulness, and technological complexity, which can affect perception of self-monitoring devices and act as deterrents to even trying self-monitoring [38]. Even among the individuals that give self-monitoring a chance, an initial positive reaction does not necessarily result in long-term use. A notable challenge to long-term self-monitoring is early abandonment of self-monitoring. Early abandonment usually occurs as the result of too much required effort, technical difficulties, discomfort with the collected information, distrust in data quality, or uselessness of the collected data. As self-monitoring increasingly involves smart phone use and cloud based storage, privacy concerns have become relevant and influence some users. [3]

Issues related to user experience, such as the appearance and comfortability of wearable devices also play a role in early abandonment [3]. A study on older adults found that fashionable and comfortable wearable devices that look like accessories, such as watches or bracelets, is an important factor encouraging use [38].

Additionally, if an individual is interested in monitoring multiple aspects of their health, for example activity and BP, they are often required to use different user interfaces. This happens because often the devices used to monitor different aspects of health are from different manufacturers and usually the use of a device requires the use of the application provided by the manufacturer. This creates challenges in the ease of monitoring the collected data. [3] This problem could be minimized by choosing devices from the same manufacturer. This would allow the access of all collected data from the same application. However, choosing the same manufacturer may not be attractive to cost conscious consumers. Additionally, the impact providing a range of devices has on device quality should be considered. Is a manufacturer that has divided their attention among several technologies able to produce comparable quality to a manufacturer focusing on a single technology? Furthermore, it should be noted that not many manufacturers have such a wide range of devices that monitoring many aspects of health would be possible with the use of just one manufacturer's devices. Another solution could be using a separate tracking application that allows the user to manually enter data [3]. This way the user can access the data from multiple sources in one place. While this approach improves the accessibility of data, it requires additional effort, which was one of the most common reasons for user abandonment.

Finally it should be recognized that the effects of long-term self-monitoring are not necessarily always positive. For example, self-monitoring of weight can lead to intensified discontent with one's body and weakened self-esteem if self-monitoring does not show progress quickly enough [11]. If the progress revealed by self-monitoring is not satisfactory, it may lead to discomfort and abandonment of self-monitoring [36]. However, in some cases this might lead to the introduction of unhealthy habits in order to facilitate desired progress faster. For example, if self-monitoring is used as a tool in weight loss, the desire for fast progress may cause an individual to implement unhealthy eating habits, such as fasting, skipping meals, or bulimic behaviour. [42]

4. EXPERIMENTAL SETUP

The experimental study involved active self-monitoring for a period of two weeks. The self-monitoring was performed by the author of the thesis, who is from this point forward referred to as participant. The aim of this experimental study was two-fold: to determine whether active self-monitoring of health has an effect on well-being during a short period of time, and to observe the challenges associated with active self-monitoring. The findings were reviewed and compared with experiences reported in literature. The self-monitoring tools and the method that were used in this study are presented in this chapter.

4.1 Tools used for self-monitoring

The self-monitoring was performed with the use of three devices manufactured by Nokia (which has now been sold back to Withings) and their mobile application designed for use with these devices. The devices included an activity tracker (Steel HR), a smart scale (Body Cardio) and a BP monitor (BPM+). The associated mobile application Health Mate was used to monitor all the recorded data.

4.1.1 Steel HR

The activity tracker (Nokia Steel HR) automatically tracks the amount of steps, burned calories, average HR, and quality of sleep. In addition, it can be used to track activities in workout mode. Workout mode includes continuous HR monitoring available in real time, and GPS tracking if the activity tracker is connected to a phone with location services enabled. The activity tracker is a smart watch that can be used to display notifications from selected smart phone applications. Additionally, the user can use it as a vibrating alarm.

The wearable activity tracker is an analogue watch with a small digital display and an activity dial, from which the user can easily see their progress on their daily step goal. These are shown in the illustration of the watch in Figure 5. The digital display can show the date and time, HR, steps, distance, calories burned during the day, notifications, battery level, and time of the next alarm. These screens are customizable, and the user may choose which screens are shown and the order of the screens based on their own preferences.

Figure 5. Photographs of the Steel HR watch that show the different components of the watch. The watch includes an analogue watch, a digital display, and an activity dial in the front, and a HR sensor in the back.

The watch uses an accelerometer to track the number of steps. The accelerometer is also used to monitor sleep and automatically detect activities, such as running or swimming. The HR is measured from the wrist using a HR sensor utilizing PPG. [43]

4.1.2 Body Cardio

The smart scale (Nokia Body Cardio) measures weight and body composition, which includes water, fat, muscle, and bone mass. In addition, the scale measures HR and PWV, which inform the user of their cardiovascular health.

The scale uses BIA to measure body composition [44]. For this reason the scale has electrodes on the surface of the scale. These electrodes can be seen in the photograph of the scale in Figure 6. Since the electrodes are used to send electric currents into the body, the scale must be used with bare feet.

Figure 6. *An edited photograph of the Body Cardio smart scale that displays the optimal placement of feet for measurements. The horizontal bands are the electrodes on the surface of the scale. The user should stand on the scale with bare feet so that their heels are on top of the second horizontal electrode.*

The scale calculates fat mass using an algorithm. The body type of an athlete is vastly different from an average person. For this reason, athletes and average people require different algorithms to calculate fat mass. Thus, the scale can be used in athlete mode if necessary. The user guide suggests using the athlete mode if the user has a resting HR of under 60 bpm and typically works out over eight hours a week.

The scale also utilizes the electrodes to measure HR and PWV, which is a measure of the propagation speed of a pressure pulse. For accurate results, these measurements require the user to stand on the scale with bare feet in a centred position and no movement during the measurement. The optimal feet placement that should be used for all of the measurements is shown in Figure 5.

4.1.3 BPM+

Nokia BPM+, is a medical device that uses the oscillometric method to measure BP [45]. The device is shown in Figure 6. The following instructions on how to properly perform a BP measurement were provided with the device. Most importantly, the BP monitor is used in a seated position and the user should rest for at least five minutes before taking a measurement. The BP monitor is placed around the upper arm and the cuff is tightened so that the BP monitor stays in place approximately 2 cm above the elbow. This device placement is visible in Figure 7. The arm is then placed on a table so that the BP monitor is at the same level as the heart.

Figure 7. *The Nokia BPM+ is placed around the upper arm approximately 2 cm above the elbow.*

The application allows the user to take a single BP measurement or an advanced BP measurement. The advanced measurement performs three measurements and gives their average as the result. If this mode is chosen, the BP monitor automatically performs the three measurements at a chosen interval.

4.1.4 Health Mate

The data collected by all the devices is available in the smart phone application Health Mate and the desktop site. The data presented in the application is divided into sections. When the aforementioned devices are in use, the sections are steps, HR, recorded activities, sleep, weight, and BP. The information about steps gives a visual representation of the steps during the day, the number of steps, the percentage of the daily goal, and the estimated distance and burned calories that are calculated by an algorithm.

The HR is shown as a graph which shows the daytime HR in blue and the HR while sleeping in grey, as shown in Figure 8. The application calculates the average HR for the day and night separately. In addition, the application displays the duration spent in each of the four HR zones: light, moderate, intense, and peak.

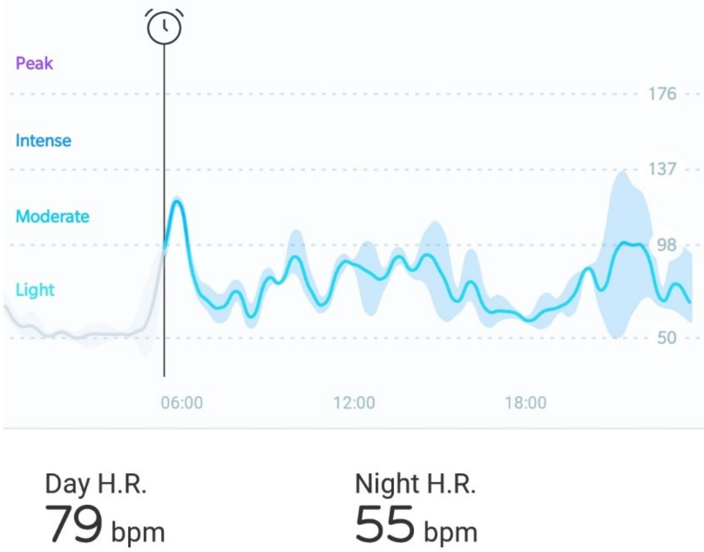

Figure 8. *The graphic display of heart rate in the Health Mate application. In the graph the HR measured during sleep is in grey and HR measured during the day is in blue. In addition, the average day and night HRs are presented below the graph.*

The sleep section provides a breakdown of the night that displays the time spent awake, and the periods of light and deep sleep. The application calculates a sleep score based on the number of interruptions during the night, and the duration, regularity, and depth of sleep. In addition, it shows the average, peak, and lowest HR recorded during the night.

For each recorded activity, the duration and estimated burned calories are shown. If workout mode was used for the activity, the recorded HR is displayed as a graph, the average HR and time spent in each HR zone is calculated. If workout mode was used with the watch connected to a phone with GPS tracking enabled, the application displays the route on a map and the pace and elevation changes as a graph. Furthermore, average pace and the recorded splits are displayed.

The information in the weight section is all displayed as graphs that show measurements over time. This section displays the recorded weight, water mass, fat mass, muscle mass, bone mass, and BMI. The body fat, muscle mass, and bone mass can be displayed as absolute weights or as a percentage. The BMI is calculated based on the recorded weight and the height inserted by the user.

The BP section shows the recorded systolic and diastolic BP the number of measurements taken, and a trend based on past measurements. Based on the recorded HR, the application gives a classification of either normal, elevated, or high.

4.2 The method

The study was performed over a period of two weeks during which the participant used the devices and the associated mobile application to actively self-monitor their health. All the available features were utilised in order to provide the participant with a well-rounded self-monitoring experience. During the study, the participant evaluated whether they felt self-monitoring had some kind of impact on their behaviour and subsequently their well-being. Additionally, the participant observed and made note of the problems they encountered.

The measurement frequency for weight and BP measurements was chosen to be twice a day, in the morning and in the evening. For BP this was chosen, as it is the measurement frequency recommended by health care professionals for home monitoring. This measurement frequency revealed the circadian pattern of BP. [46] For simplicity, the same frequency was used for weighing. This measurement frequency will also reveal the daily fluctuation of weight.

The activity tracker was worn for the whole duration of the study. Since the activity tracker has a battery life of approximately 25 days with average use, it was charged before the two week period in order to avoid having to remove it for charging during the study. The properties tracked by the activity tracker were monitored from the Health Mate application actively.

The smart scale was used in athlete mode as suggested by the user guide since the participant exercises over eight hours a week and had consistently measured their resting HR to be under 60 bpm before beginning the study. The smart scale was used to measure weight, body composition, HR, and PWV two times a day each day during the two week period, in the morning and in the evening. The aim was to perform the measurements at roughly the same time each day to obtain comparable results. The morning measurements were performed after waking up, but before breakfast, at approximately 8:00. The evening measurements were performed at approximately 21:00. These times were chosen to ensure adherence to the schedule since they are times the participant was likely to be at home most days. Health Mate allows the user to set reminders to establish a habit of taking measurements at a fixed time. These reminders were used to avoid forgetting a measurement.

In a similar manner, the BP monitor was used to measure BP twice a day each day. These measurements were performed immediately following the weighing to form two measurement sessions each day in order to make the self-monitoring as manageable as possible. The BP measurements were performed following the instructions provided with the device, described in 3.1.3. The BP was measured using the advanced measurement, in which the application automatically measures the BP three times and gives an average of these as a result. This was done to increase the accuracy of the result. The application allows the interval between consecutive measurements to be set to either 30 seconds, 1 minute, 90 seconds, or 2 minutes. A 30 second interval was used. This interval was chosen for the convenience of the participant, to minimize the time spent on measurements while still obtaining accurate results from the advanced measurement.

Since the main purpose of this study was to observe the effects of active self-monitoring, a detailed diary was kept during the study. This included any observations related to well-being, such as tiredness or feelings of stress. In addition, any problems encountered during the study were recorded so that the technical usability of self-monitoring devices can be evaluated.

5. RESULTS

The self-monitoring consisted of the collection and monitoring of a significant amount of data. Relevant details of the data and the observations about self-monitoring made by the participant are presented in this chapter.

5.1 Collected data

The collected and monitored data can be divided into categories of activity, heart health, body composition, and sleep. The data related to activity consists of the number of steps, distance, recorded activities, and burned calories. The heart health related data consists of HR, BP, and PWV measurements. The body composition data consists of weight, fat mass, bone mass, muscle mass, and hydration. The sleep data consists of duration of sleep, beginning and ending times, duration of periods of light and deep sleep, number of introductions, and awake time. The participant's sleep data is presented in Figure 9.

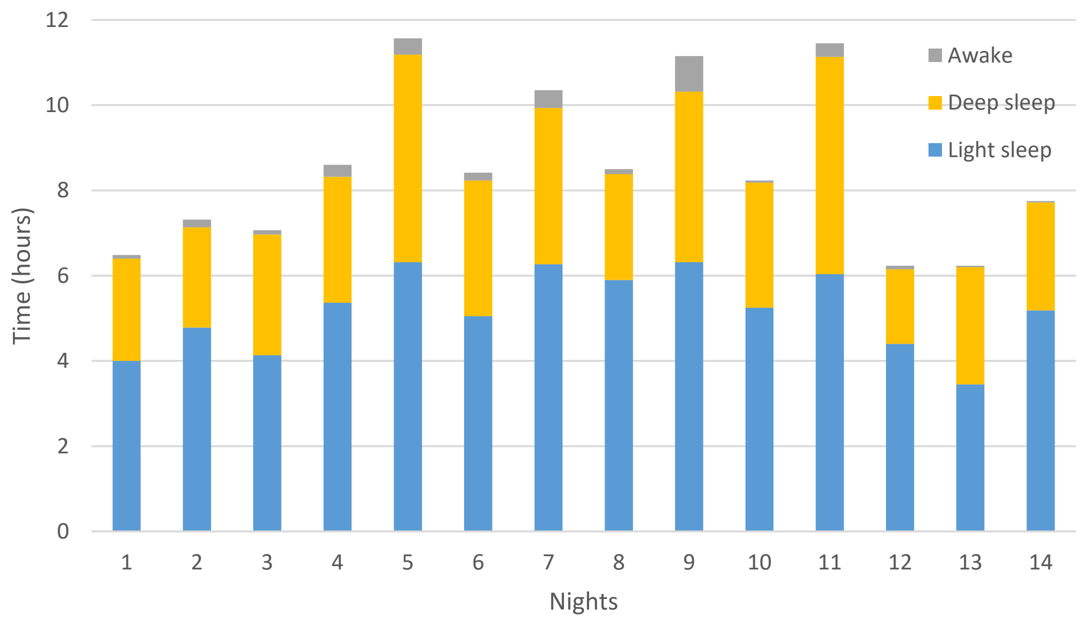

Figure 9. *Duration of sleep during each night of the self-monitoring period. Each bar represents the duration of sleep during one night. The night is divided into sections of light sleep, deep sleep, and awake time. These are displayed in blue, yellow, and grey respectively.*

In Figure 9, the bars represent the duration of sleep during one night, which is divided into sections of light sleep, deep sleep, and awake time. Light sleep is displayed in blue, deep sleep in yellow, and awake time in grey. While the duration of sleep varied substantially, the changes did not arise from the motivation to improve sleep scores determined by Health Mate. Instead the duration of sleep simply increased when the participant had the ability to sleep longer.

Besides sleep, activity was the only other metric that experienced significant variation. The number of steps per day varied between 779 and 13217. The rest of the measured metrics, such as weight, body fat, resting HR, BP, and PWV remained fairly constant. These were constantly in the healthy range and only experienced small variations from day to day. They also clearly followed circadian patterns. Generally the morning measurements produced lower values than the evening measurements. As could be expected, most of the evening measurements taken after a day of activity and eating were higher than the morning measurements taken after sleeping. For example the measurements of weight are presented in Figure 10. The morning measurements are in blue and the evening measurements in yellow.

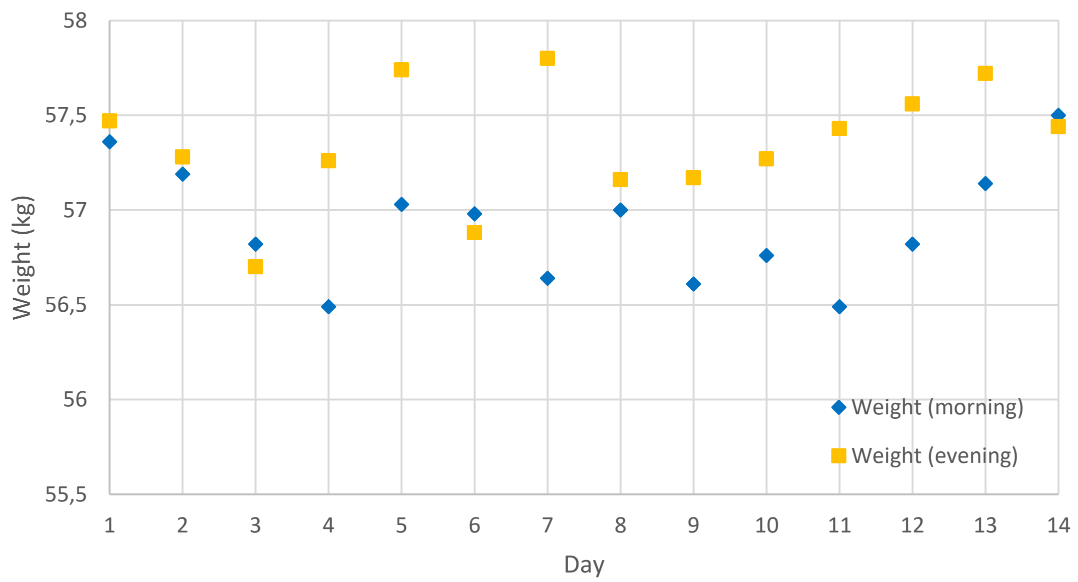

Figure 10. *Weight measurements in the morning and evening during the self-monitoring period. The morning measurements are displayed in blue and the evening measurements in yellow. With a couple of exceptions, the measurements exhibit a pattern of a lower weight in the morning and a higher weight in the evening.*

Figure 10 displays a clear pattern in the weight measurements. With the exception of days 3, 6, and 14, the measurements in the morning were lower than the measurements in the evening. BP measurements exhibited a similar trend. The BP measurements are displayed in Figure 11.

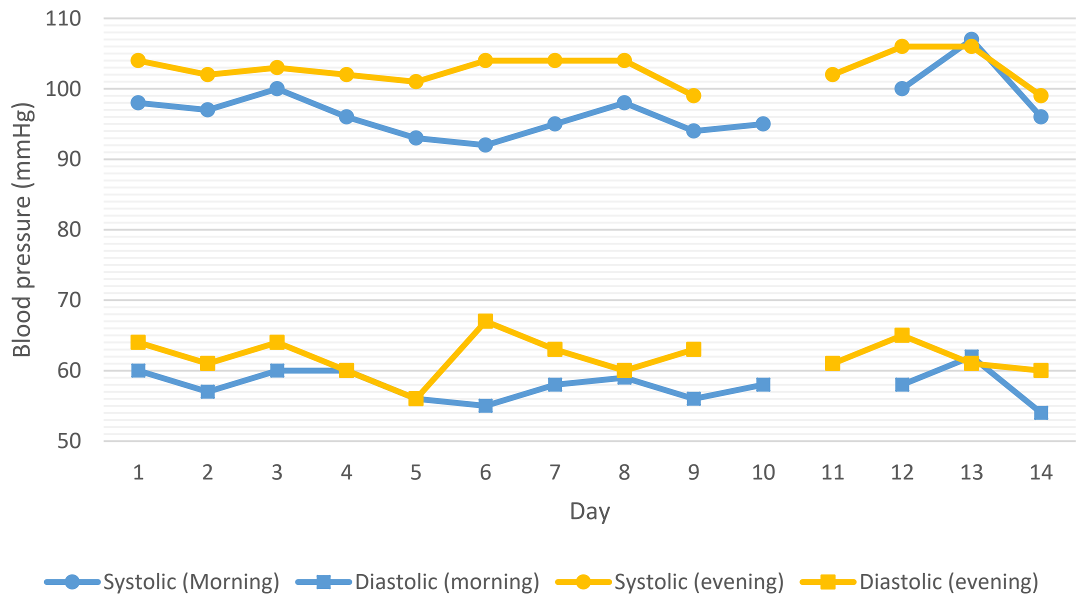

Figure 11. *The BPs measured during the self-monitoring period. The BPs measured in the morning are displayed in blue and the BPs measured in the evening are displayed in yellow. Most of the time the systolic and diastolic BPs measured in the evening were higher than in the morning.*

In Figure 11, the recorded morning and evening BPs are displayed in blue and yellow respectively. Some measurements are missing due to technical difficulties that prevented successful measurements. Similarly to weight measurements, not every evening measurement was higher than the morning measurement, but this is clearly the prevalent trend.

While most metrics followed a similar trend, body fat percentage measurements exhibited an opposite trend. The body fat percentage in the evening was consistently lower than in the morning. Since body fat percentage was measured with BIA, this can be explained by the fact that water consumption during the day results in increased water mass in the body in the evening compared to the morning.

When analysing the collected data, no significant relationships between different parameters could be identified. The only weak correlation that could be detected was between the amount and types of activity and the average HR during the day. The days that included no recorded activities exhibited the lowest average HR. Contrarily, if a day included high intensity activities, the average HR was clearly higher. This occurred as a result of high HR during activity, which then increases the average compared to a day with no activity.

5.2 Observations

Even though the self-monitoring period suddenly involved a considerable amount of self-monitoring, the participant found the process interesting and kept to it for the whole two weeks. The participant noticed clear patterns in many of the measurements, such as weight and BP. The measured values were lower in the morning and higher in the evening, as could be expected after a day of eating and activities.

In general, the participant felt that the self-monitoring did not affect their well-being. Since the weight, BP, HR, and PWV measurements were in the healthy range, the participant did not feel the need to change their behaviour in any way to improve these. Additionally the participant did not have any weight goal, and thus changes in the measured weight did not affect their behaviour either. The only time the participant noticed that the self-monitoring clearly affected their behaviour was in a situation where the participant was close to reaching their step goal for the day. In this case the participant was motivated to increase their activity in the evening enough to reach the goal, for example by going for a short walk.

Since the measured values were in the healthy range, the participant felt that performing some of the measurements was unnecessary. For example after a few consistently low BP measurements, the participant did not see any actual need to monitor BP twice a day. Were it not for the study, the participant probably would not have continued with the measurements so often. The participant felt that it would be more reasonable to perform a few days of BP measurements from time to time in order to be informed about their BP.

The participant also found the strict measurement schedule to be restricting, and even to slightly negatively affect their well-being. Since the measurement schedule was planned so that it maximized adherence to it, the morning measurements had to be scheduled to 8:00. However, on days that the participant did not have to leave home before 10:00, they thought that it would have been more beneficial for their well-being to allow longer uninterrupted sleep. Some days, the participant did resume sleeping after performing the measurements at 8:00.

While the participant mostly adhered to the set schedule, and even sometimes woke up earlier than necessary to do so, they found that it was impossible to perform every measurement at the scheduled time. The participant performed four measurement sessions at non-scheduled times. Two morning measurement sessions had to be performed much earlier because of work shifts beginning at 6:30. One evening measurement session was performed later because of losing track of time and one because of not being home yet. This made the participant realize that especially shift work makes taking comparable measurements significantly harder, or even impossible. The participant herself has previously worked morning, evening, and night shifts in rotation, and currently works occasional shifts. When working three different shifts, performing measurements at some set time is impossible as there is no one time that could be used every day. Additionally even if only a general time frame is used, the measurements are still highly incomparable, since performing morning measurements after working a night shift or after eight hours of sleep do not produce comparable results. However, in such a situation self-monitoring could provide useful insights into how night shift affects health and how an individual recovers after a night shift. However, the participant did not have a night shift during the two week period. Thus, while this aspect was thought provoking, the effects of a night shift to measurements could not be analysed.

The most notable issues the participant noticed were technical difficulties and inaccuracies in measured data. During the two week period, the participant experienced various technical difficulties. The technical difficulties included problems during the installation of the smart scale, with the use of the smart scale and the BP monitor, and with running out of batteries from the BP monitor.

The technical difficulties began before the official start of the two week period, when preparing the smart scale for use. The installation process required either setting up a Wi-Fi connection or choosing to use Bluetooth to sync the information between the scale and the smart phone application. The participant attempted to set up a Wi-Fi connection but the scale was not able to connect to the Wi-Fi. The application provided instructions on how to attempt fixing the situation, but none resulted in a successful connection. Fortunately, connection via Bluetooth was successful, and the unavailable functions when using this mode were insignificant, such as displaying the weather.

Another technical difficulty with the scale occurred after a week of use. Since the scale had been borrowed for the duration of the study, the scale had been used by other users. This meant that the scale remembered the data of other users and connected the measurement to the correct user based on the measured weight. The problem was caused by having two people with very similar weights. Up to this point, the scale had asked the user to choose the correct user. However, one evening the weight of the participant was a little higher than generally and the scale would not give the user the choice of users, instead automatically connecting the measurement with the incorrect user. After trying to repeat the measurement several times, the user gave up and decided to perform trouble shooting the following day. The participant was discouraged by the lack of information in the help and frequently asked questions sections provided by the manufacturer. The solution that was suggested did not resolve the issue. Even a factory reset did not help. Finally the problem was resolved by dissociating the product from all other accounts, but this was a solution that was not suggested in the help section and would not be practical if the scale was in active use by other people, for example family members. This resulted in missing two body composition and PWV measurements. The weight measurements were obtained and entered manually into the application.

Another less significant technical difficulty was unsuccessful PWV measurements. This occurred during a third of the measurements during the two week period causing the minor inconvenience of having to repeat measurements. The reason for the failure of these measurements was probably small movements during the measurement.

The problems with the use of the BP monitor were mostly failures in measurements. This occurred 4 times during the two week period. The participant found this to be much more frustrating than the failures with the scale. The BP was measured three times with 30 second intervals between measurements. The measurements failed once during the second measurement and two times during the last measurement and once after the last measurement had seemingly been completed. In the case that the application gave an error notice, the application would not even record the successful measurements that had occurred before the error. For this reason, the participant had to repeat the measurements in order to get any record of the measurement. Even though the additional time requirement was only approximately five minutes, the participant found repeating the measurements extremely frustrating. Additionally, especially in the morning this could also create rush, as the participant did not necessarily have five extra minutes. In such as situation, a normal person would most likely skip the measurement after failure. If the measurements were not done for study purposes, the participant would have done the same.

Another technical problem with the BP monitor occurred when the BP monitor ran out of batteries. This would not have been a problem if the user had noticed that the battery was low in advance and prepared for this by purchasing spare batteries. However, the application gave a noticeable warning of low battery only when it could no longer perform even a single measurement. It should be noted that there might have been a warning that the participant missed. However, in order to provide a pleasant user experience this kind of warning should be visible enough that it does not get lost amongst all the other data in the application. In this case the required batteries where type AAA, which are common and often found in households. Thus, this scenario might not have resulted in a problem at all had the participant had spare batteries available. However, at this time the participant had no spare batteries, which resulted in the inability to perform measurements. Since this occurred in the evening, the subsequent morning measurements were also missed for the same reason before new batteries could be acquired.

The only technical problem with the activity tracker was its inability to continuously measure HR in workout mode. During almost every workout, there were periods during which the activity tracker was unable to determine HR. This occurred despite the fact that the watch was placed on the wrist according to given instructions.

The participant noticed inaccuracies in the measured data in three separate scenarios. The first and most frequent inaccuracy occurred during workouts. When using the activity tracker in workout mode, the activity tracker measures HR continuously and this can be monitored by the user in real time. Of course the validity of the measurements in general were in no way tested, but the participant noticed that several times when they knew their HR was high (above 150 bpm), the activity tracker measured HRs of 60 to 80 bpm. This measurement was so off that the user could easily notice the discrepancy.

The second inaccuracy in measured data occurred in the measurements of body composition. The user scale had consistently measured the participant’s body fat percentage to be approximately 17%, but two measurements claimed that the participant’s body fat percentage was 30%. This had to be some sort of error, as such an increase in body fat percentage is in no way realistic in the span of one day. This error is probably due to both measurement error and unreliability of BIA in general.

The third data inaccuracy involved sleep tracking. While the activity tracker detected accurately the beginning and ending times of sleep during the night, the activity tracker did not detect shorter periods of sleep during the day. This occurred with both short and long naps of over two hours.

6. DISCUSSION

It should be noted that the experimental study performed had limitations. The three most notable limitations were the number of participants being one, the participant being the author herself, and the duration of the experimental study being only two weeks. The limited size means that the study does not provide reliable information of the population as a whole. Additionally, the participant being the author probably improved self-monitoring adherence and persistence with technical difficulties. Finally, the limited duration does not accurately reflect the long-term aspect of self-monitoring. Despite this, the study did provide useful insights related to self-monitoring and revealed similar benefits and challenges to those found in literature.

The participant's observations were in many areas in agreement with the available literature. For example they found that experiencing technical difficulties discouraged the use of the devices. Had the self-monitoring not been conducted as a part of a study, this could have resulted in not performing measurements, and potentially in longer breaks from measurements or even complete abandonment of the use of the particular device. Additionally, the participant experienced moments in which they doubted the accuracy of the measurements. This resulted in doubt concerning all of the collected data and affected the perceived usefulness and definitely did not encourage continuation of use.

At times, the participant also felt that performing the measurements was not useful. This is also an issue reported in literature. In this case the uselessness was associated with the lack of any goal related to the measurements. For example, since the participant did not have any particular weight loss or management goal, they did not feel the need for such frequent measurements. Additionally, the fact that measured values were in a health range made subsequent measurements feel unnecessary. For example, after finding out that their BP was in a healthy range, the participant did not feel the need to continue BP measurements. This is reasonable, and reflects the suggestions of health care professionals, who suggest self-monitoring BP in 7-day periods [46].

However, not all of the participant's observations reflect literature. The participant did not find that active self-monitoring had a noticeable effect on their well-being. Many studies have shown the use of an activity tracker to increase physical activity. The participant's observations do not reflect this. The already regular physical activity of the participant before use of an activity tracker may affect this. Additionally, the fact that the period of self-monitoring was short and coincided with an increased work load most probably hindered the effects active self-monitoring had on physical activity. Another factor that may have led to not noticing any changes in well-being was the lack of behavioural change caused by self-monitoring. The lack of behavioural change was caused by measurements consistently falling in the healthy range. As a result, the participant did not see any need to change behaviour to improve them. Sleep was the only parameter that would have benefited from behavioural change. However, despite the occasionally short nights and low sleep scores, the participant was not able to increase their amount of sleep during these shorter nights.

The only case in which the self-monitoring had an effect on the participant's behaviour was when they were close to reaching their daily step goal. In this situation, the participant increased their activity in the evening in order to reach the goal. This demonstrates how activity trackers are able to motivate users and reflects findings in literature that found activity tracker use to increase physical activity. However, this only happened once during 14 days. Instead, there were several days when the participant was inactive and far from reaching the daily step goal. In these cases monitoring of activity and reaching the goal did not motivate the participant to increase activity. This occurred because the participant knew they would not actually achieve the goal, so they did not bother increasing activity at all to get closer to the goal. For this reason it is important to choose a goal that is achievable if the purpose of self-monitoring is to change behaviour. Choosing an achievable goal motivates the user, while a too ambitious goal will not have the same effect.

7. CONCLUSIONS

Long-term self-monitoring of health has the possibility to be beneficial for well-being and health. Especially long-term self-monitoring of activity and weight result in positive outcomes and the continuously emerging novel devices and smart phone applications for self-monitoring are broadening the possibilities of self-monitoring. Since much of self-monitoring technology is relatively novel, studies concerning the effects of long-term use of many of the available self-monitoring devices are still scarce.

While long-term self-monitoring is considered beneficial, it faces significant challenges. The most notable challenge is early abandonment of self-monitoring devices. A significant number of new users do not continue to use self-monitoring devices in the long run. The reasons for giving up the use of self-monitoring devices include technical difficulties, excessive amount of effort required, unreliability of collected data, perceived uselessness, privacy concerns, and discomfort with what self-monitoring detects. These issues should be addressed in order to improve device usability and user experience, which would hopefully decrease early abandonment of self-monitoring devices.

The self-monitoring landscape is in constant change and the future of self-monitoring seems promising. Technological advancements are making self-monitoring health related parameters easier and more reliable. While self-monitoring is still rather separate from health care, self-monitoring shows promise in this area. For example, data collected by self-monitoring could be uploaded into healthcare information systems and subsequently utilized by healthcare professionals in diagnosis and treatment planning. Self-monitoring is already an important part in the management of some chronic diseases and could be used to facilitate a shift to more personalized healthcare that focuses on preventive actions and increased active participation in the management of one’s own health.

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